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"What drives regional differences in BMI? Evidence from Spain"

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Abstract

This paper aims to contribute to the debate on the North–South health divide, by disentangling the conditioning factors that account for regional differences in BMI. Based on the Spanish data of the European Health Survey of 2014, we first decompose the average BMI gap between the North and the South of Spain into the contribution of the explained and unexplained factors, using the Oaxaca-Blinder decomposition. We also carry out a distributional analysis by applying the Recentered Influence Function (RIF) Regression and the corresponding decomposition, to analyse BMI differentials along its unconditional distribution. We consider the case of Spain, which is a country characterized by important geographical disparities in BMI and other health outcomes, as well as by the decentralized structure of the Spanish National Health System (NHS). Indeed, this is the first paper that estimates and decomposes the underlying factors responsible for regional BMI variation in European countries. Our findings indicate that North to South differences in mean BMI are significant only for women and a large share (64%) of this gap is explained by differences in endowments (basically years of schooling) to the detriment of women living in the South. Moreover, the explained (unexplained) portion of the gap steadily increases (decreases) along the BMI distribution, revealing that what really matters to deal with the obesity epidemic among overweight women is focusing attention on regional disparities in endowments, human capital being the main driver.

Keywords: Obesity, Regional BMI variation, Decomposition analysis, Spain.

JEL Classification: I12, I14, R28

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1. Introduction

The rapid increase of overweight and obesity around the globe has raised concerns both from a health perspective and from an economic point of view, as it represents a risk factor for several chronic diseases that affect labour market performance and increase health care expenditure. The latest data show that the global annual medical cost of treating obesity-related diseases is expected to reach 1.2 trillion US$ by 2025 (World Obesity Federation, 2017). Moreover, worldwide the proportion of adults who are obese and overweight has generally increased over recent years. A recent study (GBD Obesity collaborators, 2017) analysed data from 68.5 million people with a view to assessing the trends in the prevalence of overweight and obesity among children and adults between 1980 and 2015. According to their results, the prevalence of obesity has doubled in more than 70 countries and has been continuously increasing in most other countries since 1980. In a similar vein, a study estimating trends in adult Body Mass Index (BMI) in 200 countries from 1975 to 2014 finds that the global age-standardized mean BMI increased from 21.7 kg/m^2 in 1975 to 24.2 kg/m^2 in 2014 in men and from 22.1 kg/m^2 in 1975 to 24.6 kg/m^2 in 2014 in women (NCD-RisC, 2016).

Spain is one of the countries experiencing high trends in the prevalence of overweight and obesity compared to the OECD average (OECD, 2014). Specifically, 1 out of 6 adults is obese and more than 1 out of 2 is overweight (including obese) in Spain. Notwithstanding, strong regional discrepancies in excess body weight exist within the country, i.e., the residents of some regions exhibiting much higher average BMI rates than others (Gutiérrez-Fisac et al., 1999; Valdes et al., 2014; Raftopoulou, 2017). Geographical disparities in health outcomes have been observed in other countries as well. For example, Ellis and Fry (2010) consider several health indicators, including life expectancy, childhood obesity, cancer deaths, smoking and alcohol consumption to document the existence of a divide between northern and southern regions of the UK, in favour of the latter. This result is also confirmed by Hacking et al. (2011), showing a northern excess in all-cause mortality which remained substantial and persistent over the four decades from 1965 to 2008 in England, and affecting many more males than females.

Investigating the existence and magnitude of a North–South gap in BMI and analysing the underlying determinants of such health disparities across Spanish regions could be especially relevant for public health policy-makers, in their intent to meet the WHO target of halting the rise of obesity to its 2010 level by 2025 (Global Action Plan, WHO 2017). In addition, as health care competences in Spain are in the hands of regional authorities, this introduces additional heterogeneity in the way this epidemic is tackled across regions making this country an especially relevant case for such an analysis. More specifically, in contexts where the NHS is decentralized and health competences are primarily the responsibility of the country's regions, as in the case of Spain, local decision-makers need to have evidence on health indicators at the regional level. Therefore, the ultimate goal of this paper is to produce evidence regarding the drivers of regional disparities in BMI for the Spanish case. After all, policies against overweight and obesity may be better designed at the regional level taking advantage of knowledge of the local culture and population circumstances (Oates, 1972).

More specifically, in this paper we analyse and decompose regional differentials in BMI between northern and southern Spanish regions[1]. First, by means of OLS regression, we analyse the relationship between BMI and several potential conditioning factors (basically sociodemographic attributes, socioeconomic status, and lifestyle characteristics), and examine whether their conditional correlation with BMI is different between the two groups of regions. Second, we decompose the observed average gap into the part attributed to differences in observable determinants of BMI (i.e. the endowments) and the part that is left unexplained and is due to differences in the return to observable characteristics, using the classical Oaxaca-Blinder (OB) decomposition.

Moreover, as long as important differences in BMI occur away from the average, we proceed with a distributional analysis by applying the Recentered Influence Function (RIF) regression. The RIF regression enables obtaining evidence along the unconditional distribution of BMI, which is especially important for the design of health and food policies. Indeed, policy-makers are interested in targeting policies to

[1] A spatial pattern of BMI has been observed in Spain, such that Southern regions exhibit on average higher BMI levels than Northern ones. Based on this spatial heterogeneity, we analyse the BMI gap between these two groups of regions.

individuals who are (unconditionally) either underweight or obese, rather than those who appear in the two cues of the conditional distribution of BMI (i.e. whether they are obese or underweight given their characteristics). Therefore, our main contribution lies in the fact that we decompose regional differences in BMI along its unconditional distribution into the contribution of the endowment of observable characteristics and the return to those characteristics. This way, we are able to observe what happens at every part of the distribution and subsequently draw conclusions for the more interesting tails: the upper one (obesity, severe obesity)[2] and the lower (underweight) where relationships might vary. The analysis is carried out separately by gender, as the underlying mechanisms that affect BMI and health in general might be very different for women and men. Indeed, it is essential to consider the gender dimension when designing interventions to enhance health conditions.

Our findings indicate that the South to North differences in BMI are mostly driven by women, whereas it is lower and not statistically significant for men (0.55 points, z-stat 3.3 for females relative to 0.128 points, z-stat 0.88 for males). Around 64% of the cross-regional gap in BMI among women is accounted by differences in observable characteristics. More specifically, women residing in the South have lower education, employment rates and income levels. The distributional analysis reveals that the South to North gap in BMI for Spanish women tends to increase over its unconditional distribution, with observable factors (especially schooling) making a growing contribution in explaining the differential across the quantiles of BMI. The rest of the paper proceeds as follows: in Section 2, we review the relevant existing literature, in Section 3 we present the data on BMI and report some descriptive statistics. Section 4 contains the details of the empirical methodology and Section 5 describes and discusses the estimation results. The conclusions are reported in Section 6.

[2] The WHO defines obesity as a BMI ≥ 30 kg/m^2, while severe obesity corresponds to BMI ≥ 40 kg/m^2.

2. Related Literature

Two lines of research can be distinguished within the health economics literature and specifically the economics of obesity, where decomposition methods have been extensively employed. The first is linked to the well-known literature on socioeconomic-related health inequalities[3] and refers to a set of studies aimed at quantifying and decomposing the extent of inequalities in obesity risk via the calculation of concentration indexes. This research, mostly focused on developed countries, tends to show that obesity is mainly concentrated among the poor, and inequality varies over time, with education, demographics, income and life-style being its main contributors (e.g. Zhang and Wang, 2004; Costa-Font and Gil, 2008; Nikolaou and Nikolaou, 2008; Ljungvall and Gerdtham, 2010; Hajizadeh et al., 2014; Davillas and Benzeval, 2016). The second line of research includes those studies concerned with decomposing average BMI differentials by applying the Oaxaca-Blinder method (Dutton and McLaren, 2011; Sen, 2014) or examining the entire BMI distribution using conditional quantile regression (Costa-Font et al., 2009).[4]

Our paper is related to the latter group of studies that analyse BMI differentials, adopting a geographical perspective. Although our study is not the first in decomposing BMI differentials (Costa-Font et al., 2009; Costa-Font et al., 2010; Dutton and McLaren, 2011), we do contribute to the literature by performing a *detailed* decomposition based on the RIF method. To our knowledge, this is the first work that provides similar evidence for European countries. Dutton and McLaren (2017) used a similar technique utilizing Canadian data to examine the importance of individual-level characteristics for explaining geographic variation in BMI distributions. They also perform quantile regression and the corresponding decomposition, however focusing only on the aggregated effects. We move a step further by presenting the detailed decomposition of the relevance of specific key factors for the design of interventions

[3] See for instance Kakwani et al. (1997), Wagstaff et al. (2003) and van Doorslaer and Koolman (2004).

[4] This tool has also been applied to other health issues such as differences in objective health indices (Heger, 2016) or in low birth weight (Lhila and Long, 2012).

targeting overweight individuals (such as age, sex, education or lifestyle habits) in accounting for the regional gap in BMI.

From the methodological point of view, our study is mostly based on the contributions of two seminal papers (Oaxaca, 1973; Blinder, 1973), which present a method to decompose inter-group differences in the mean levels of an outcome into explained (i.e. difference in the endowment of observable characteristics) and unexplained (i.e. difference in the returns to those characteristics) factors using the OLS regression estimates. This method has been widely applied within the field of labour economics when decomposing average wage differentials by gender or ethnicity (c.f., Reimers, 1983; O'Neill and O'Neill, 2006). However, an important limitation of this approach is the focus on average gaps, thus neglecting important differences at other points of the outcome's distribution.[5] Therefore, subsequent developments extended the decomposition methods to other moments than the mean, or even to the whole distribution of the outcome (Freeman, 1980, 1984; Juhn et al., 1993; DiNardo et al., 1996; Machin and Meghir, 2000; Machado and Mata, 2005).[6]

In this paper, we apply a method that was proposed by Firpo et al. (2009), where the (Recentered) Influence Function (RIF) for the distribution statistic of interest is used – instead of the usual outcome variable – as the left-hand side variable in a regression. The basic advantages of this analysis are twofold. First, it is not affected by path dependency, and second, it enables a detailed decomposition. That is, applying the OB decomposition to the RIF allows disentangling the observed gap along the unconditional distribution of BMI into the contribution of composition and returns effects of single covariates (or group of covariates) included in the model. It seems worth noting that the use of the RIF-Regression decomposition is especially relevant in our framework, since providing evidence on the unconditional distribution of BMI makes the analysis much more informative for policy-makers who are interested in designing policies addressed

[5] Another drawback of the Oaxaca-Blinder (OB) decomposition is that it is path-dependent, which means that the decomposition relies on the ordering of the explanatory variables.

[6] This set of approaches does have some drawbacks though. For example, the DFL (DiNardo et al., 1996) method does not allow detailed decomposition, while the MM (Machado and Mata, 2005) approach that is based on the decomposition of differences along the conditional distribution suffers from the problem of path-dependence on top of being computationally demanding.

to those who are either over- or underweight (not "conditionally" to over- or underweight).[7]

3. Data and Descriptive Statistics

This paper draws on data from the 2014 wave of the Spanish version of the *European Health Interview Survey (EHIS)*, which covers the population aged 15 or more and contains several sociodemographic and health-related variables that are crucial for our purposes. Moreover, the Spanish data of the EHIS survey are representative at the regional level (NUTS2) level, which enables examining regional disparities in BMI and their determinants as we do in this paper. The original sample contains 22,842 observations. We keep only individuals born in Spain who are aged 18-65 at the time of the survey with valid information on the relevant variables.[8] We also discard observations from the islands of Spain (Balearic and Canary Islands), as well as the autonomous cities of Ceuta and Melilla that are located on the northern coast of Africa.[9]

Mostly following the existing literature on BMI, we divide the conditioning factors into three main groups, namely 1) sociodemographic variables, 2) socioeconomic status (SES), and 3) lifestyle variables (see Appendix: Table A). Specifically, we consider several dummies for age cohorts, the number of children in the household and a dummy for being married for the first group of controls. For the second group we proxy socioeconomic status with years of schooling, equivalent family net income in levels and with a dummy variable for being employed. Since both lifestyles and food habits have been identified as key obesity-risk factors in the literature, we also include indicators for sedentary behaviour at work, physical activity during leisure time, daily

[7] i.e., with very high or very low residuals, given the observed characteristics.

[8] The exception is the equivalent family income variable, which is missing for a non-trivial proportion of the sample. In order to avoid selectivity bias due to the non-random non-reporting of the income variable, we consider missing income as an additional category of the original variable.

[9] Ceuta and Melilla were excluded due to their very low representativeness in the dataset, as were the Balearic and Canary Islands since we assume they may have different influences due to their geographical position in contrast to Spanish inland territory.

smoking, alcohol consumption[10] and consumption of meat, fruits, vegetables and legumes as our last group of controls.[11]

Figure 1 exhibits average BMI by ACs for the pooled sample and by gender. It is evident that the North to South divide is mostly driven by females, for whom geographical differences in BMI are much more pronounced. Since our aim consists in disentangling the BMI between northern and southern Spanish regions, we divided Spain into three groups. The group named "South" consists of the regions or Autonomous Communities of Andalusia, Extremadura and Murcia and the second group, named "North", comprises Asturias, Cantabria, Galicia, Navarra, the Basque Country and Rioja. The remaining continental Spanish regions are considered to form part of the centre of the country and are excluded from our empirical analysis. This grouping assumes intragroup homogeneity but intergroup heterogeneity. Table 1 shows the resulting two groups of regions, with the corresponding observations contained in the estimation sample and some basic descriptive statistics for BMI. We report a statistically significant difference of 0.36 units in mean BMI between the South (25.97 kg/m^2) and the North (25.63 kg/m^2).

[Figure 1 & Table 1 around here]

3.1 Descriptive statistics

Tables 2 and 3 report the sample means of the BMI indicator and its determinants differentiating by regional group, for women and men respectively. As can be appreciated, there are substantial differences in the endowment of characteristics between the two groups of regions, which are generally significant from a statistical point of view and more pronounced for women.

More specifically, in Table 2, we document a large and significant difference in mean weight level of around 1.650 kg (average height is more or less the same) between

[10] Amount of weekly alcohol consumption (in grams).

[11] Specifically, we measured the consumption of fruits, vegetables and legumes (meat) of between 4 to 6 times per week or higher intakes (less than once per week or never) as high (low) frequency of consumption.

women in the South and the North. As a result, the South to North BMI gap amounts to a significant 0.55 kg/m^2 (0.12 standard deviations apart). In terms of household composition, a higher proportion of females in the South are married compared to those living in the North. Interestingly, the data show the existence of a large and significant difference in years of schooling, with females residing in the North having almost 1.5 extra years of schooling (12.01 vs 10.52). Similarly, noticeable differences to the detriment of females living in the South exist regarding income and working status endowments. More specifically, they have a lower mean income level in comparison to the other group, as well as a much lower employment share (44% vs 60%). With respect to lifestyle characteristics, women in the South are less likely to work in a sedentary job compared to their counterparts in the North, and they tend to exercise more during leisure time, are more likely to smoke on a daily basis and drink less alcohol per week. In terms of food habits, women in the South tend to consume less red meat (25% vs 35%) and less fruit. Differences in the consumption of vegetables and legumes among women are not statistically significant between the two groups of regions.

Table 3 exhibits the same descriptive statistics for males. Interestingly, we evidence the absence of any significant difference in BMI, body weight or height status across the two areas. Less remarkable differences in endowments between the South and the North are shown as well. With respect to household composition, a higher proportion of men in the South are married in comparison to men living in the North. Differences in schooling are to the detriment of males living in the South (10.10 vs 11.22 years), while the same applies regarding income and working status endowments. In terms of lifestyle characteristics, similarly to women, men in the South tend to exercise more during leisure time and to smoke more. With respect to food habits, men in the South tend to eat less red meat (29% vs 39%) and more vegetables (62% vs 58%).

[Tables 2 and 3 around here]

4. Empirical Methodology

4.1 Average BMI Differentials between groups of regions.

Since the descriptive statistics alone do not give us a clear picture of the ceteris paribus effects, nor the contribution of each factor on the BMI difference between the groups, we proceed first by running a simple OLS regression which explains BMI as a function of a vector of control variables (X_i) divided into the three main groups we mentioned before, namely 1) sociodemographic variables, 2) SES, and 3) lifestyle variables. We estimate the equation separately for Southern and Northern regions, that is,

$$bmi_i^S = \alpha^S + \beta^S X_{iS} + u_i^S \tag{1a}$$

$$bmi_i^N = \alpha^N + \beta^N X_{iN} + u_i^N \tag{1b}$$

where the superscripts S and N indicate that the corresponding estimates are allowed to be different for South and North, respectively. Next, with the aim of appreciating the contribution of the covariates on the observed BMI disparities between the groups of regions, we utilize the Oaxaca-Blinder (OB) decomposition (Oaxaca, 1973; Blinder, 1973). This widely used decomposition method disentangles average outcome differentials into the contribution of the (average) endowment of observable characteristics (i.e. the explained or composition component) and the contribution of unexplained factors or structure effect (which is captured by differences in the estimated coefficients). Furthermore, as suggested by Fortin (2008) and Fortin et al. (2011), we estimate the non-discriminatory reference BMI structure from a pooled regression with all the selected regions together, imposing an identification restriction that ensures that the BMI advantage of one group of regions equals the disadvantage suffered by the other group, that is:

$$bmi_i = \alpha + \beta' X_i + \gamma_N I(N=1) + \gamma_S I(S=1) + u_i \tag{2}$$
$$subject\ to\ \ \gamma_S + \gamma_N = 0$$

Equation (2) is estimated using the pooled sample, and contains indicators for belonging to the North or South (N = 1 if North, S = 1 if South). The estimated vector of β coefficients thus represents the non-discriminatory BMI structure that is used in the decomposition. From the estimates of equation (2) we decompose the raw BMI differentials between the groups of regions into different components as follows:

$$\overline{bm\imath^S} - \overline{bm\imath^N} = \left(\overline{X^S} - \overline{X^N}\right)\hat{\beta} + (\hat{\gamma}_S - \hat{\gamma}_N) + E[u_i|N = 1] - E[u_i|S = 1] =$$
$$= \left(\overline{X^S} - \overline{X^N}\right)\hat{\beta} + [\underbrace{\left(\overline{X^S}\left(\hat{\beta}_S - \hat{\beta}\right) + (\hat{\alpha}_S - \hat{\alpha})\right)}_{\hat{\gamma}_S} - \underbrace{\left(\overline{X^N}\left(\hat{\beta}_N - \hat{\beta}\right) + (\hat{\alpha}_N - \hat{\alpha})\right)}_{\hat{\gamma}_N}]$$

(3)

The term $\left(\overline{X^S} - \overline{X^N}\right)\hat{\beta}$ represents the composition effect (i.e. share of average BMI gap due to differences in observable characteristics), whereas the term $(\hat{\gamma}_S - \hat{\gamma}_N) = \left(\overline{X^S}\left(\hat{\beta}_S - \hat{\beta}\right) + (\hat{\alpha}_S - \hat{\alpha})\right) - \left(\overline{X^N}\left(\hat{\beta}_N - \hat{\beta}\right) + (\hat{\alpha}_N - \hat{\alpha})\right)$ corresponds to the part of the mean BMI differential that can be attributed to different coefficients or returns to observable characteristics across regions (including the intercept). Notice that the effect of differences in unobservables across regions are also included here.[12]

4.2 Distributional BMI Differentials

Nevertheless, both the regression analysis and the OB decomposition provide evidence about average BMI differences across the groups of regions. As already mentioned in the introduction by focusing only on average gaps one may miss important differences that could occur at other points of the BMI distribution (especially at the top, corresponding to obesity and severe/morbid obesity categories). Therefore, we investigate distributional BMI differences by means of the Unconditional Quantile Regression (UQR) method proposed by Firpo et al. (2009). The UQR is based on the statistical concept of the Influence Function (IF), which represents the influence of an individual observation on a distributional statistic of interest (e.g. the quantile). By adding back the statistic to the corresponding IF, it is possible to obtain the Recentered Influence Function (RIF) for each quantile of the outcome. The RIF Regression estimates the marginal effects of a set of characteristics on an unconditional distributional statistic of an outcome variable. The RIF for the τth quantile (q_τ) of BMI corresponds to,

[12] Notice that the term $E[u_i|N = 1] - E[u_i|\mathrm{S} = 0]$ is assumed to be zero, which corresponds to the standard OLS hypothesis of orthogonality between the error term and the regressors (in this case, the dummies for South/North BMI regions). Moreover, it seems worth commenting that the OB decomposition can be further divided into the contribution of each specific covariate (detailed decomposition), which can eventually also be aggregated into subgroups (as explained later). However, the presence of categorical variables makes the results of the detailed decomposition dependent on the choice of the reference category. This issue can be avoided by "normalizing" the effects of discrete covariates as explained in Jann (2008).

$$RIF(bmi_i, q_\tau) = q_\tau + IF(bmi_i, q_\tau) = q_\tau + \frac{\tau - I(bmi_i \leq q_\tau)}{f_{bmi_i}(q_\tau)} \quad (4)$$

where $f_{bmi_i}(q_\tau)$ is the unconditional density of BMI evaluated at the τth quantile and I(·) an indicator function. By replacing the unknown elements of equation (4) by their sample estimators it is possible to obtain an estimate of the RIF, which is,

$$\widehat{RIF}(bmi_i, q_\tau) = \hat{q}_\tau + \widehat{IF}(bmi_i, q_\tau) = \hat{q}_\tau + \frac{\tau - I(bmi_i \leq \hat{q}_\tau)}{\hat{f}_{bmi_i}(\hat{q}_\tau)}$$

(5)

where $\hat{f}_{bmi}(\hat{q}_\tau)$ corresponds to a Kernel density estimator of the unconditional density function of the outcome. The RIF for a given quantile can be taken as a linear approximation of the nonlinear function of the quantile, and captures the change of the (unconditional) quantile of the outcome in response to a change in the underlying distribution of the covariates (Firpo et al., 2009). It can be shown that the expected value of the RIF for selected quantiles of the unconditional distribution of BMI ($\hat{q}_\tau$) can be modelled to be a linear function of explanatory variables, as in a standard linear regression.

Given the linear approximation of the conditional expectation of the RIF and the theoretical property stating that the average $\overline{RIF}(bmi_i, \hat{q}_\tau)$ is equal to the corresponding marginal quantile of the distribution of the outcome, it is possible to generalize the standard OB decomposition of average outcomes to a distributional decomposition applied to the unconditional distribution of the outcome (see Firpo et al., 2009 and Fortin et al., 2011 for technical details). In other words, it is possible to examine the contribution of both the endowment of observable characteristics and the returns to these characteristics, in explaining the estimated unconditional BMI gap across groups of regions, applying the decomposition for average outcomes described by equation (3) to the RIF, that is:

$$\hat{q}_{S\tau} - \hat{q}_{N\tau} = \overline{RIF}(bmi^S, \hat{q}_\tau) - \overline{RIF}(bmi^N, \hat{q}_\tau) \; =$$

$$\left(\overline{X^S}-\overline{X^N}\right)\hat{\beta}_\tau+\left[\left(\overline{X^S}\left(\hat{\beta}_{S\tau}-\hat{\beta}_\tau\right)+\left(\hat{\alpha}_{S\tau}-\hat{\alpha}_\tau\right)\right)-\left(\overline{X^N}\left(\hat{\beta}_{N\tau}-\hat{\beta}_\tau\right)+\left(\hat{\alpha}_{N\tau}-\hat{\alpha}_\tau\right)\right)\right]$$

(6)

Here $\hat{\beta}_\tau$ corresponds to the nondiscriminatory BMI structure (estimated from a pooled RIF regression) at quantile τ estimated in a similar fashion as equation (2). Similar to equation (3), the term $\left(\overline{X^S}-\overline{X^N}\right)\hat{\beta}_\tau$ represents the composition effect and the term $\left(\overline{X^S}\left(\hat{\beta}_{S\tau}-\hat{\beta}_\tau\right)+\left(\hat{\alpha}_{S\tau}-\hat{\alpha}_\tau\right)\right)-\left(\overline{X^N}\left(\hat{\beta}_{N\tau}-\hat{\beta}_\tau\right)+\left(\hat{\alpha}_{N\tau}-\hat{\alpha}_\tau\right)\right)$ captures the unexplained component of BMI differential evaluated at the τ-quantile of the unconditional distribution of BMI. There are several advantages of this method. Its computational cost is minimal and it provides path independent detailed decompositions of both components.

5. Results

5.1 OLS BMI estimates

Table 4 shows the OLS estimates of the BMI determinants separately for the South and the North and distinguishing by gender. The findings point out the existence of a heterogeneous pattern of correlates between BMI and its covariates both across regions and by gender. That is, control variables affect individual BMI differently depending on the group of regions the person belongs to and on whether they are females or males. Certainly, Table 4 evidences a positive age gradient in mean BMI in both regions and for both genders, however this effect is comparatively stronger for females (males) residing in Southern (Northern) regions (standardized beta coefficients: 0.22 (0.25) vs 0.16 (0.10)). In terms of household composition, being married is only significant for men in the South group of regions, while number of children in the household is a significant control (with a negative impact on BMI) only for women and men in Northern regions. Schooling exerts the expected negative effect on mean BMI. Its effect is similar for females residing in the North and in the South, but for males tends to be stronger in the former area of the country (standardized beta coefficient -0.15 in the North vs -0.08 in the South). On the contrary, family income barely affects BMI regardless of geographical location and gender.

Statistically significant coefficients and with the expected sign are also found for other key BMI determinants. More specifically, working in a sedentary job has a positive and statistically significant conditional association with BMI for females in both areas of the country, although for males this variable is only significant in the South. Regarding physical activity during leisure time, the estimates for females indicate a negative association with BMI only in Northern regions, whereas for males doing sports at least once per week is negatively associated with BMI, with a stronger effect in the South. Finally, daily smokers exhibit lower BMI levels, as widely reported in the literature (Dare et al., 2015), although affecting men to a greater extent than women.

[Table 4 around here]

5.2 OB Decomposition Results

Tables 5 and 6 present both the aggregated and detailed OB decomposition results respectively, differentiating by gender. The decomposition analysis shown in Table 5 evidences that up to 64% (0.35 BMI units) of the overall South to North mean BMI gap for women (0.55 BMI units) is due to differences in endowments (the explained part), whereas the remaining 36% (0.20 BMI units) is due to the differences in coefficients or returns to BMI determinants and unobservables (the unexplained part). This finding indicates that a policy intervention addressed to equalize certain endowments across regions (particularly schooling) would reduce the mean BMI gap among women quite significantly. Interestingly, the results show that while the explained part is mostly driven by more disadvantaged SES endowments of women living in the South, both socio-demographics and lifestyle characteristics are to the detriment of females living in the North. Moving on to the detailed decomposition (see Table 6), we identify differentials in average years of schooling as by far the single most important contributor in explaining the greater mean BMI level for Southern women. Differences in income and working status are also relevant factors in the explained part to the detriment of women in the South, but with a more modest contribution. In contrast, healthy (unhealthy) lifestyles such as weekly sport activities (sedentary job) and low consumption of meat (daily smoking), as well as the number of children in the household are in favour of women living in the South (though their contribution is low). As shown in Table 6, as a whole, the unexplained part or returns to certain characteristics (including unobserved effects)[13], which accounts for 37% of the total gap for females, is not statistically significant.

The OB decomposition analysis suggests that the average BMI differential across regions for males is small (0.13 BMI points) and insignificant. Schooling remains the most important contributor in differences in endowments favouring men in the North. We detect a small but statistically significant positive contribution of marital status and income level in explaining the composition effect, while a lower share of meat consumption but a greater proportion of physical exertion (those healthy habits with a negative sign in Table 6) would act to reduce the explained part, hence favouring Southern individuals. For males, the explained part is not significant because the better endowment of SES factors of residents in northern regions tends to compensate for the less favourable composition in terms of sociodemographic and lifestyle characteristics. Moreover, although there is also a significant difference in the return to sociodemographic factors, it is compensated by a negative difference in the intercept. The returns to vegetables' consumption, marital status and the number of children in the household are detrimental for men residing in the South and hence increase the mean BMI gap (see Table 6).[14]

In what follows, we move a step ahead from the simple decomposition of average differentials and, by means of RIF-regressions, we disentangle the factors behind the North–South gap for males and females over the entire unconditional distribution of BMI.

[Tables 5 and 6 around here]

5.3 RIF Decomposition Results

[13] By virtue of the ignorability assumption, unobservable determinants of BMI are supposed to be the same across regions.

[14] The positive contribution of the coefficient of number of children to the mean BMI gap is explained by the highly negative influence of this control on mean BMI for Northern individuals (see Table 3).

Tables 7 and 8, as well as Figure 1, present the aggregated RIF decomposition results separately for women and men at the different deciles of the unconditional distribution of BMI, while the detailed RIF-decomposition results are reported in Tables B and C of the Appendix.[15] First of all, in line with previous findings regarding mean differentials, we obtained no evidence of significant regional gaps at any point of the BMI distribution for men. Thus, observed differences between the South and the North of Spain must be solely attributed to women. Secondly, the estimated cross-regional BMI gap for women tends to increase as we move along the distribution. That is, larger BMI differences in women between the two sets of regions are found in the upper part of the distribution, that is, in the segment of the BMI distribution that reflects overweight and obesity problems. Thirdly, the data also reveal that the explained (unexplained) portion of the gap steadily increases (decreases) over the quantiles, revealing that what really matters to deal with the obesity epidemic among overweight women is to focus the attention on regional disparities in endowments. Note that the contribution of differences in observable characteristics is always statistically significant and reaches its highest value at the 8th decile, which corresponds to high levels of overweight or pre-obesity status among women.

The pattern regarding the separate contribution of groups of covariates is in line with what we obtained from the decomposition of average differentials. It seems worth noticing the significant increase in the role played by SES across the distribution of BMI. More specifically, the positive contribution of observable characteristics is mainly driven by schooling, while income and employment status also contribute to the explained part of the difference. We show that schooling is the main contributor throughout the BMI distribution whereas, on the contrary, food habits (mainly meat consumption) are detrimental for women in the North. While women in the North are worse off with respect to their lifestyle habits (eating habits and physical activity), they have much more advantaged endowments with respect to their SES status and, as a result, they exhibit lower BMI values. Overall, the unexplained factors are significant at the bottom tail, while most of the difference at the higher parts of the distribution is

[15] Tables B and C in the Appendix exhibit the detailed RIF decomposition results for the top three deciles of the unconditional distribution of BMI for women and men respectively. This is because these deciles are the most interesting for our purposes, because they correspond to overweight and obesity statuses. Detailed results for all the deciles are available upon request.

attributed to explained factors. The evidence from the RIF decomposition suggests that policies aimed at enhancing women's human capital in the South of Spain could reduce the prevalence of overweight and obesity problems and favour convergence to the relatively lower values observed in northern Spanish regions.

[Tables 7, 8 and Figure 1 around here]

6. Conclusion and Discussion

This paper investigates the conditioning factors behind the North–South BMI divide in Spain. The OLS results show that the conditional correlation between observable determinants of BMI differs in the two groups of regions (North vs South) and by gender. We proceed with a decomposition analysis that enables us to disentangle the contribution of each covariate and the corresponding coefficients to this difference. Starting with the OB decomposition, we reveal that the mean BMI gap between the South and North of Spain is mostly driven by differences between women residing in the two areas of the country. The findings also evidence that a large and significant part of this regional average gap in BMI (64%) is due to differences in endowments related to SES status (basically years of education), whereas differences in returns to such characteristics and play a minor and insignificant role in accounting for the observed BMI differential. Indeed, in view of the epidemic of obesity as a global public health concern, policy-makers are mostly interested in designing effective policies against the overweight and obese. Hence, we proceed with the distributional analysis and the corresponding decomposition, since the findings at the upper tail of the BMI distribution are the ones actually capturing overweight and obesity problems. Interestingly, we evidence that differences in SES endowments and particularly schooling explain a very significant part of the women's North to South differential (accounting for up to 90% of the gap at the 8th decile) at the top of the BMI distribution.

Therefore, a significant part of the cross-regional BMI gap can be mitigated by implementing the right policies focused on improving human capital, which would be more effective if combined with government actions that encourage and support healthy living. Efforts aimed at improving (years of) schooling for women in the South would substantially mitigate differences in overweight and obesity between the two groups of regions. Moreover, specific interventions aiming at giving people advice on a healthy diet and physical activity (information that can also be transmitted from parents to their offspring), or improving labelling on food and drink to help people make healthy choices are some of the recommended actions. Indeed, implementing these kinds of informative interventions at school (i.e. nutrition and food education programmes) is also a sensible route to follow. Such a policy intervention would additionally reduce differences in obesity-related diseases and/or improve health in general, inasmuch as obesity constitutes a key risk factor for many chronic conditions and health complications (e.g., type 2 diabetes, heart diseases, some types of cancer, high blood pressure, high cholesterol). However, it must also be stressed that even equalizing the female endowments across the two groups of regions, there would still be a certain differential in BMI that penalizes southern Spanish regions in terms of the prevalence of overweight and obesity problems.

Altogether, our results indicate that SES differentials (mainly educational attainment) between women residing in the North versus their counterparts living in the South of the country are producing remarkable differences in a specific health variable (BMI in our case) across these regions, both at the mean and at the top of the distribution. This is in line with the evidence from existing related research, suggesting that regional inequalities in education are responsible for regional health inequalities. For example, Ergin and Kunst (2015) argue that health differentials exist between the West and the East of Turkey and are mainly explained by differences in SES characteristics and mostly education. In a similar vein, Safaei (2014) reports health disparities between Canadian health regions along education and income dimensions. Ballas et al. (2012) report that inequalities in education between regions observed in several EU countries tend to reinforce inequalities between income, wealth, social status and health, contributing to persistent inter-regional disparities. How educational inequalities translate into income, employment and health disparities through a complex set of mechanisms is a research question beyond the aims of this work. Moreover, albeit in this specific paper we do not provide causal evidence, the results exhibit a very strong conditional correlation between education and BMI, being the endowment of the former variable responsible for a substantial share of the gap in BMI between women residing in different Spanish regions. Indeed, this is consistent with the causal evidence obtained by Brunello et al. (2013) for several European countries, indicating that exogenous increases in schooling generate a protective effect for females (but no such causal impact is found for males). Therefore, the causal effect of education in mitigating regional disparities in BMI, overweight and obesity and even other health-related variables should be further investigated in future research.

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Tables of Results

Table 1: Groups of regions

	Sample size	%	Mean BMI	S.D. BMI
		South		
Andalucía	1.694	58.21	26.044	4.582
Extremadura	620	21.31	26.026	4.324
Murcia	596	20.48	25.713	4.332
Total	**2.910**	**100**	**25.972**	**4.478**
		North		
Asturias	553	16.04	26.180	4.616
Cantabria	446	12.94	25.761	4.471
Galicia	723	20.97	26.430	4.816
Navarra	530	15.38	25.157	4.094
Basque Country	818	23.73	25.090	4.323
Rioja	377	10.94	24.974	3.957
Total	**3.447**	**100**	**25.631**	**4.461**

Table 2: Descriptive BMI determinants for Women

	South		North		
Variables	Mean	*s.d.*	Mean	*s.d.*	Diff. South-North
Height	162.09	*6.40*	161.82	*6.33*	0.266
Weight	66.17	*12.09*	64.53	*12.33*	1.641***
BMI	25.22	*4.62*	24.68	*4.79*	0.545***
Sociodemographic characteristics					
Age: 18-35	0.24	*0.42*	0.22	*0.41*	0.021
Age: 36-45	0.28	*0.45*	0.26	*0.44*	0.017
Age: 46-55	0.26	*0.43*	0.26	*0.44*	-0.003
Age: 55-65	0.21	*0.41*	0.24	*0.43*	-0.034**
Male					
Household composition					
Married	0.62	*0.48*	0.58	*0.49*	0.043**
Kids	0.58	*0.83*	0.44	*0.74*	0.137***
Socioeconomic status					
Schooling	10.52	*4.53*	12.01	*4.27*	-1.495***
Income1	0.27	*0.44*	0.12	*0.33*	0.143***
Income2	0.22	*0.41*	0.16	*0.36*	0.060***
Income3	0.21	*0.41*	0.22	*0.41*	-0.007
Income4	0.09	*0.29*	0.18	*0.38*	-0.087***
Income5	0.04	*0.20*	0.07	*0.26*	-0.031***
Income6	0.14	*0.35*	0.22	*0.41*	-0.078***
Working	0.44	*0.49*	0.60	*0.48*	-0.157***
Lifestyle variables					
Sedentary job	0.27	*0.44*	0.32	*0.46*	-0.042***
Weekly sport activities	0.10	*0.30*	0.08	*0.27*	0.024**
Daily smoker	0.27	*0.44*	0.23	*0.42*	0.041***
Weekly alcohol consumption (index)	2.26	*5.15*	3.15	*6.16*	-0.885***
Food habits variables					
Meat	0.25	*0.43*	0.35	*0.47*	-0.099***
Fruit	0.76	*0.42*	0.80	*0.39*	-0.042***
Vegetables	0.74	*0.43*	0.73	*0.44*	0.011
Legumes	0.06	*0.24*	0.05	*0.22*	0.010
Number of observations	**1.493**		**1.766**		

Table 3: Descriptive BMI determinants for Men

	South		North		
Variables	mean	*s.d.*	mean	*s.d.*	Diff. south-north
Height	174.20	*7.13*	174.27	*6.85*	-0.074
Weight	81.16	*13.21*	80.90	*12.61*	0.259
BMI	26.75	*4.17*	26.62	*3.83*	0.128
Sociodemographic characteristics					
Age: 18-35	0.26	*0.43*	0.19	*0.39*	0.065***
Age: 36-45	0.27	*0.44*	0.26	*0.44*	0.004
Age: 46-55	0.27	*0.44*	0.26	*0.44*	0.009
Age: 55-65	0.19	*0.39*	0.26	*0.44*	-0.078***
Male					
Household composition					
Married	0.60	*0.48*	0.57	*0.49*	0.036**
Kids	0.53	*0.82*	0.39	*0.72*	0.145***
Socioeconomic status					
Schooling	10.10	*4.10*	11.22	*4.01*	-1.123***
Income1	0.25	*0.43*	0.10	*0.30*	0.156***
Income2	0.23	*0.42*	0.17	*0.37*	0.063***
Income3	0.21	*0.41*	0.23	*0.42*	-0.013
Income4	0.11	*0.31*	0.19	*0.39*	-0.088***
Income5	0.05	*0.22*	0.07	*0.27*	-0.027***
Income6	0.12	*0.33*	0.21	*0.41*	-0.092***
Working	0.60	*0.48*	0.64	*0.47*	-0.048***
Lifestyle variables					
Sedentary job	0.32	*0.46*	0.32	*0.46*	-0.004
Weekly sport activities	0.16	*0.36*	0.13	*0.33*	0.030**
Daily smoker	0.34	*0.47*	0.30	*0.46*	0.038**
Weekly alcohol consumption (index)	8.93	*13.38*	9.70	*14.02*	-0.770
Food habits variables					
Meat	0.29	*0.45*	0.39	*0.48*	-0.100***
Fruit	0.70	*0.45*	0.69	*0.46*	0.012
Vegetables	0.62	*0.48*	0.58	*0.49*	0.039**
Legumes	0.05	*0.23*	0.07	*0.27*	-0.023**
Number of observations	**1.417**		**1.681**		

Table 4: BMI estimations: OLS Results

	Women		Men	
	South	**North**	**South**	**North**
Constant	26.650***	27.008***	26.005***	27.023***
	(0.522)	*(0.624)*	*(0.449)*	*(0.480)*
Sociodemographic characteristics				
Age: 18-35 (reference category)	-	-	-	-
Age: 36-45	0.548	0.572	1.141***	1.709***
	(0.351)	*(0.320)*	*(0.317)*	*(0.285)*
Age: 46-55	1.457***	1.204***	1.356***	2.295***
	(0.349)	*(0.337)*	*(0.320)*	*(0.281)*
Age: 55-65	2.491***	1.171**	1.786***	2.198***
	(0.404)	*(0.399)*	*(0.367)*	*(0.296)*
Household composition				
Married	0.392	0.495	0.977***	0.171
	(0.276)	*(0.263)*	*(0.281)*	*(0.222)*
Kids	-0.194	-0.565***	0.145	-0.448**
	(0.164)	*(0.156)*	*(0.164)*	*(0.142)*
Socioeconomic status				
Schooling	-0.228***	-0.268***	-0.089**	-0.145***
	(0.035)	*(0.036)*	*(0.031)*	*(0.027)*
Income1 (reference category)	-	-	-	-
Income2	0.289	-0.160	0.713*	-0.140
	(0.340)	*(0.446)*	*(0.334)*	*(0.408)*
Income3	-0.121	-0.419	0.029	0.110
	(0.342)	*(0.447)*	*(0.361)*	*(0.400)*
Income4	-0.123	-0.998*	-0.653	-0.191
	(0.460)	*(0.454)*	*(0.397)*	*(0.413)*
Income5	-0.405	-1.380*	-0.045	0.258
	(0.502)	*(0.560)*	*(0.496)*	*(0.514)*
Income6	-0.078	-0.842*	-0.125	-0.203
	(0.383)	*(0.422)*	*(0.395)*	*(0.397)*
Working	-0.479	-0.224	-0.413	0.221
	(0.248)	*(0.240)*	*(0.262)*	*(0.221)*
Lifestyle variables				
Sedentary job	0.655*	0.774**	0.711**	0.220
	(0.276)	*(0.261)*	*(0.248)*	*(0.201)*
Weekly sport activities	-0.421	-0.764*	-1.142***	-0.883***
	(0.342)	*(0.324)*	*(0.243)*	*(0.225)*
Daily smoker	-0.564*	-0.575*	-0.853***	-0.800***
	(0.262)	*(0.261)*	*(0.235)*	*(0.214)*
Weekly alcohol consumption (index)	-0.046*	0.001	0.005	0.000
	(0.020)	*(0.017)*	*(0.008)*	*(0.007)*
Food habits variables				
Meat	0.518	0.261	0.280	0.415*
	(0.284)	*(0.231)*	*(0.252)*	*(0.187)*
Fruits	-0.156	0.682*	-0.133	-0.155
	(0.299)	*(0.284)*	*(0.256)*	*(0.214)*
Vegetables	0.167	0.286	0.535*	-0.366
	(0.267)	*(0.258)*	*(0.228)*	*(0.192)*
Legumes	-0.289	-1.293**	0.098	0.220
	(0.409)	*(0.443)*	*(0.503)*	*(0.366)*
R-squared	0.157	0.141	0.111	0.109
Number of Observations	1.493	1.766	1.417	1.681

Note: South comprises the regions of Andalusia, Extremadura and Murcia, whereas North comprises Asturias, Cantabria, Galicia, Navarra, the Basque Country and Rioja. Standard errors in parenthesis. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Table 5: Oaxaca Decomposition (Aggregated Results)

	Women		Men	
Overall decomposition	Mean BMI	z-stat	Mean BMI	z-stat
South regions	25.23	210.79	26.76	241.13
North regions	24.68	216.27	26.63	284.63
BMI Difference (south-north)	**0.55**	**3.3**	**0.128**	**0.88**
Explained difference	**0.35**	**4.16**	**-0.04**	**-0.58**
Sociodemographic characteristics	-0.09	-2.70	-0.13	-3.44
SES	0.54	8.26	0.19	4.24
Lifestyle	-0.11	-3.14	-0.11	-3.72
Unexplained difference	**0.20**	**1.19**	**0.17**	**1.16**
Sociodemographic characteristics	0.11	0.47	0.73	3.79
SES	0.23	0.38	0.27	0.58
Lifestyle	-0.73	-1.67	0.65	1.86
Constant	0.59	0.74	-1.48	-2.29

Table 6: Oaxaca Decomposition (Detailed Results)

	Women				Men			
Overall Decomposition	Mean BMI		z-stat		Mean BMI		z-stat	
South regions	25.227		210.79		26.758		241.13	
North regions	24.68		216.27		26.629		284.63	
BMI Difference (south-north)	**0.55**		**3.3**		**0.128**		**0.88**	
	Explained		**Unexplained**		**Explained**		**Unexplained**	
	Coef.	**z-stat**	**Coef.**	**z-stat**	**Coef.**	**z-stat**	**Coef.**	**z-stat**
	0.35	**4.16**	**0.19**	**1.19**	**-0.41**	**-0.58**	**0.17**	**1.16**
Sociodemographic characteristics	-0.09	-2.70	0.1	0.47	-0.01	-3.44	0.73	3.79
Age: 18-35	-0.02	-1.38	-0.09	-1.25	-0.08	-3.92	0.11	1.79
Age: 36-45	-0.00	-0.95	-0.11	-1.34	0.00	0.22	-0.02	-0.32
Age: 46-55	-0.00	-0.21	-0.03	-0.50	0.00	0.57	-0.12	-1.89
Age: 55-65	-0.03	-2.10	0.21	2.65	-0.05	-3.51	0.02	0.25
Married	0.02	1.64	-0.06	-0.27	0.02	1.65	0.48	2.27
Kids	-0.05	-2.81	0.19	1.64	-0.01	-0.92	0.27	2.69
SES	0.55	8.26	0.23	0.38	0.02	4.24	0.27	0.58
Schooling	0.37	6.94	0.45	0.81	0.14	4.75	0.59	1.38
Income1	0.05	1.58	-0.11	-1.36	-0.01	-0.19	0.01	0.10
Income2	0.03	2.16	-0.02	-0.33	0.02	1.96	0.17	2.67
Income3	-0.00	-0.40	-0.06	-0.83	-0.00	-0.57	-0.02	-0.34
Income4	0.02	1.26	0.04	0.91	0.03	2.36	-0.07	-1.64
Income5	0.02	1.94	0.02	0.93	-0.00	-0.41	-0.02	-0.78
Income6	0.01	0.72	0.04	0.63	0.01	0.85	0.01	0.23
Working	0.06	2.03	-0.13	-0.76	0.00	0.36	-0.40	-1.86
Lifestyle variables	-0.10	-3.14	-0.73	-1.67	-0.01	-3.72	0.65	1.86
Sedentary job	-0.03	-2.16	-0.04	-0.32	-0.00	-0.25	0.16	1.54
Weekly sport activities	-0.01	-1.75	0.03	0.74	-0.03	-2.20	-0.04	-0.79
Daily smoker	-0.02	-2.00	0.00	0.03	-0.03	-2.06	-0.02	-0.16
Weekly alcohol consumption (index)	0.02	1.41	-0.12	-1.82	-0.00	-0.34	0.04	0.42
Meat	-0.04	-2.03	0.08	0.72	-0.03	-2.27	-0.04	-0.42
Fruits	-0.01	-1.22	-0.66	-2.05	-0.00	-0.55	0.01	0.06
Vegetables	0.00	0.63	-0.09	-0.32	0.00	0.46	0.55	3.03
Legumes	-0.01	-1.09	0.06	1.66	-0.00	-0.64	-0.01	-0.19
Constant			0.59	0.74			-1.48	-2.29

Table 7: Quantile Decomposition (Women)

	quantile 0.1	quantile 0.2	quantile 0.3	quantile 0.4	quantile 0.5	quantile 0.6	quantile 0.7	quantile 0.8	quantile 0.9
South	20.09	21.37	22.41	23.39	24.39	25.55	26.91	28.69	31.58
z-stat	168.46	185.75	186.4	181.5	170.52	159.5	150.97	128.47	94.76
North	19.73	20.84	21.80	22.71	23.75	24.85	26.24	27.96	31.17
z-stat	208.47	206.84	207.22	203.65	189.81	173.13	154.92	136.29	112.92
BMI Difference (south-north)	**0.36**	**0.54**	**0.61**	**0.69**	**0.64**	**0.70**	**0.67**	**0.73**	**0.40**
z-stat	2.35	3.50	3.81	4.02	3.38	3.27	2.73	2.40	0.93
Explained difference	**0.09**	**0.13**	**0.18**	**0.21**	**0.28**	**0.42**	**0.50**	**0.64**	**0.69**
z-stat	1.43	1.88	2.41	2.53	3.08	4.07	4.43	4.71	3.83
Sociodemographics	-0.02	-0.04	-0.05	-0.09	-0.11	-0.12	-0.10	-0.11	-0.15
z-stat	-0.77	-1.13	-1.29	-2.27	-2.67	-2.87	-2.65	-2.50	-2.79
SES	0.14	0.19	0.26	0.36	0.50	0.63	0.73	0.88	1.04
z-stat	3.16	4.00	5.20	6.43	7.42	8.14	7.93	7.92	6.91
Lifestyle habits	-0.03	-0.03	-0.03	-0.06	-0.11	-0.09	-0.12	-0.13	-0.19
z-stat	-1.09	-0.96	-1.04	-1.84	-3.03	-2.39	-2.67	-2.36	-2.39
Unexplained difference	**0.27**	**0.41**	**0.43**	**0.48**	**0.36**	**0.29**	**0.17**	**0.09**	**-0.29**
z-stat	1.68	2.59	2.65	2.81	1.91	1.34	0.68	0.28	-0.67
Sociodemographics	0.38	0.16	0.18	0.03	0.28	0.32	-0.06	0.10	-0.22
z-stat	1.71	0.72	0.81	0.12	1.10	1.11	-0.20	0.24	-0.38
SES	0.08	-0.12	-0.30	0.03	0.02	-0.62	-0.08	0.86	-0.03
z-stat	0.17	-0.25	-0.59	0.06	0.03	-0.90	-0.11	0.85	-0.02
Lifestyle habits	-0.86	-0.96	-0.61	-0.30	-0.55	-0.53	-0.12	-1.53	-1.22
z-stat	-1.86	-2.27	-1.43	-0.65	-1.09	-0.93	-1.81	-1.90	-1.09
Constant	0.66	1.33	1.15	0.71	0.61	1.11	1.48	0.65	1.17
z-stat	0.97	1.97	1.66	0.95	0.74	1.16	1.32	0.46	0.57

Table 8: Quantile Decomposition (Men)

	quantile 0.1	quantile 0.2	quantile 0.3	quantile 0.4	quantile 0.5	quantile 0.6	quantile 0.7	quantile 0.8	quantile 0.9
South	22.24	23.55	24.49	25.26	26.15	27.18	28.39	29.76	31.97
z-stat	162.56	215.24	229.44	221.28	207.14	199.04	190.13	158.26	127.92
North	22.45	23.57	24.41	25.21	26.03	27.09	28.07	29.42	31.65
z-stat	208.72	250.88	263.26	253.03	235.31	218.53	214.79	186.26	148.16
BMI difference (south-north)	**-0.21**	**-0.02**	**0.07**	**0.05**	**0.12**	**0.09**	**0.33**	**0.34**	**0.32**
z-stat	-1.20	-0.12	0.52	0.35	0.71	0.50	1.64	1.40	0.96
Explained difference	**-0.17**	**-0.01**	**-0.04**	**-0.07**	**-0.08**	**-0.06**	**-0.04**	**-0.06**	**0.02**
z-stat	-2.07	-0.14	-0.57	-1.03	-0.98	-0.71	-0.42	-0.46	0.10
Sociodemographics	-0.12	-0.09	-0.09	-0.13	-0.13	-0.16	-0.16	-0.19	-0.19
z-stat	-2.61	-2.40	-2.61	-3.30	-3.23	-3.56	-3.50	-3.71	-3.19
SES	0.01	0.11	0.13	0.14	0.17	0.23	0.24	0.26	0.34
z-stat	0.16	2.67	3.04	3.06	3.39	3.96	3.88	3.46	3.34
Lifestyle habits	-0.05	-0.03	-0.07	-0.08	-0.11	-0.13	-0.12	-0.13	-0.14
z-stat	-1.88	-1.41	-3.01	-3.11	-3.66	-3.70	-3.26	-2.79	-2.28
Unexplained difference	**-0.04**	**-0.00**	**0.13**	**0.12**	**0.20**	**0.15**	**0.37**	**0.40**	**0.30**
z-stat	-0.23	-0.05	0.76	0.81	1.12	0.81	1.78	1.55	0.89
Sociodemographics	0.79	0.67	0.64	0.52	0.64	0.77	0.88	0.64	0.50
z-stat	3.44	3.44	3.41	2.59	2.89	3.17	3.42	1.99	1.12
SES	0.21	0.06	-0.16	0.52	0.49	0.10	0.01	0.11	0.01
z-stat	0.37	0.14	-0.33	1.05	0.88	0.17	0.02	0.14	0.01
Lifestyle habits	-0.15	0.23	0.27	0.70	0.93	1.10	0.93	0.85	1.22
z-stat	-0.36	0.65	0.78	1.90	2.28	2.46	1.95	1.41	1.52
Constant	-0.89	-0.96	-0.64	-1.61	-1.86	-1.81	-1.46	-1.20	-1.43
z-stat	-1.22	-1.64	-1.08	-2.52	-2.59	-2.28	-1.70	-1.09	-0.91

Graph 1: Average BMI per region and by gender

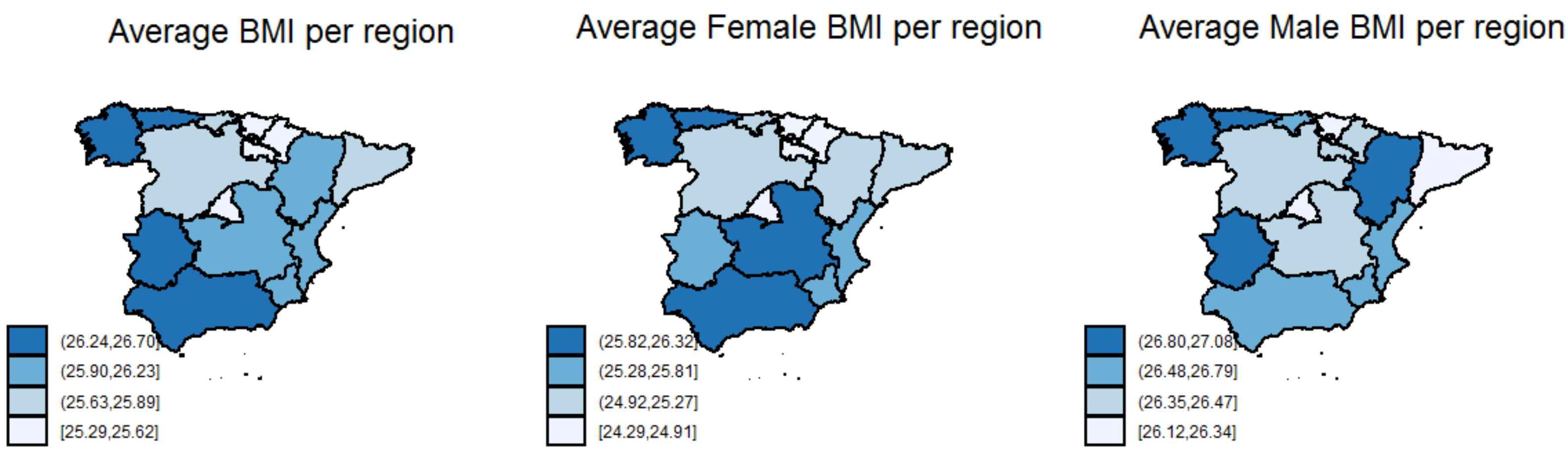
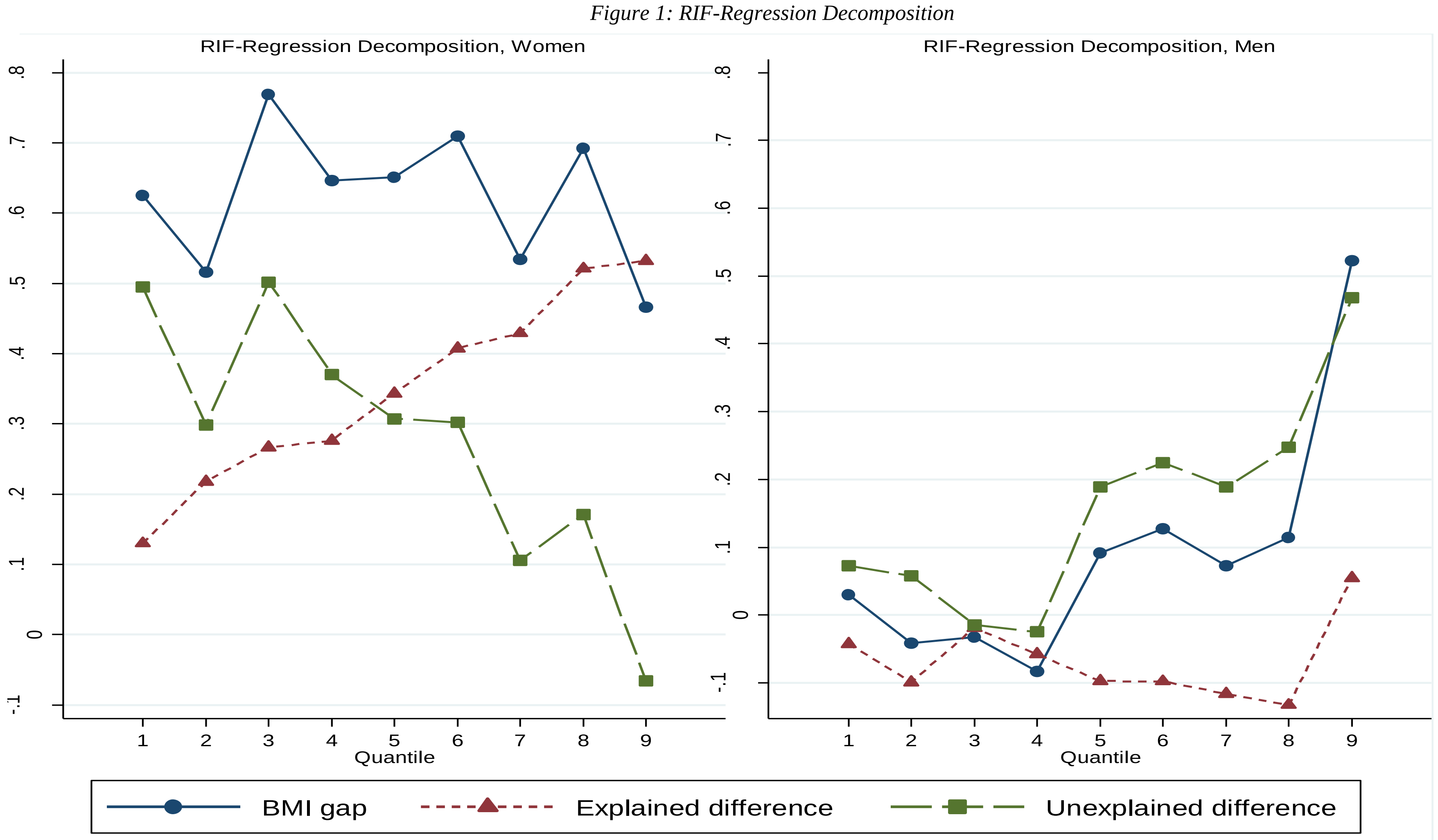


Figure 1: RIF-Regression Decomposition



Appendix

Table A: Description of dependent and independent variables

Variables	**Description**
Dependent Variable	
BMI	weight in kg divided by height in meters squared ((kg) / [height (m)]^2)
Independent Variables	
Demographics	
Age: 18-35	1 when aged 18-35 , 0 otherwise
Age: 36-45	1 when aged 36-45, 0 otherwise
Age: 46-55	1 when aged 46-55, 0 otherwise
Age: 55-65	1 when aged 55 65, 0 otherwise
Male	1 when male, 0 otherwise
Married	1 when married, 0 otherwise
Kids	number of children in the household
SES	
Schooling	years of schooling (derived by the education level)
Income1	family income lower than 970 euros
Income2	family income ranges from 970 to 1400 euros
Income3	family income ranges from 1401 to 2040 euros
Income4	family income ranges from 2041 to 3280 euros
Income5	family income is higher than 3280
Income6	missing family income
Working	1 if working, 0 otherwise
Lifestyle variables	
Sedentary job	1 if working in a sedentary job, 0 otherwise
Weekly sport activities	1 if doing a physical activity many times per week, 0 otherwise
Daily smoker	1 if daily smoker, 0 otherwise
Weekly alcohol consumption (index)	daily alcohol consumption (in grams)
Meat	1 if consumes meat more than 4 times per week, 0 otherwise
Fruits	1 if consumes fruit more than 4 times per week, 0 otherwise
Vegetables	1 if consumes vegetables more than 4 times per week, 0 otherwise
Legumes	1 if consumes legumes more than 4 times per week, 0 otherwise

Table B: Detailed RIFR Decomposition (Women)

	quantile 0.7		quantile 0.8		quantile 0.9	
	mean BMI	***z-stat***	**mean BMI**	***z-stat***	**mean BMI**	***z-stat***
South	26.91	*150.97*	28.69	*128.47*	31.57	*94.76*
North	26.24	*154.92*	27.96	*136.29*	31.17	*112.92*
	Coef.	***z-stat***	**Coef.**	***z-stat***	**Coef.**	***z-stat***
BMI Difference (south-north)	**0.67**	***2.73***	**0.73**	***2.40***	**0.40**	***0.93***
Explained difference	**0.50**	***4.43***	**0.64**	***4.71***	**0.69**	***3.83***
Sociodemographics	-0.09	*-2.65*	-0.11	*-2.50*	-0.14	*-2.79*
Age: 18-35	-0.19	*-1.34*	-0.01	*-1.18*	-0.02	*-1.26*
Age:36-45	-0.00	*-0.63*	-0.08	*-0.90*	-0.00	*-0.48*
Age:46-55	-0.00	*-0.21*	-0.00	*-0.19*	-0.00	*-0.21*
Age: 55-65	-0.03	*-1.89*	-0.03	*-1.80*	-0.03	*-1.36*
Married	0.02	*1.25*	0.03	*1.56*	0.00	*0.20*
Kids	-0.06	*-2.38*	-0.08	*-2.64*	-0.09	*-2.25*
SES	**0.73**	***7.93***	**0.88**	***7.92***	**1.03**	***6.91***
Schooling	0.47	*6.68*	0.53	*6.30*	0.65	*5.60*
Income1	0.08	*1.89*	0.12	*2.18*	0.14	*1.77*
Income2	0.03	*1.99*	0.05	*2.24*	0.05	*1.69*
Income3	-0.00	*-0.37*	-0.00	*-0.18*	0.00	*0.31*
Income4	0.02	*0.68*	0.06	*2.33*	0.07	*1.88*
Income5	0.03	*2.42*	0.03	*2.06*	0.03	*1.52*
Income6	-0.00	*-0.08*	-0.00	*-0.12*	0.00	*0.17*
Working	0.09	*2.08*	0.08	*1.59*	0.09	*1.23*
Lifestyle habits	**-0.12**	***-2.67***	**-0.13**	***-2.36***	**-0.19**	***-2.39***
Sedentary job	-0.03	*-1.98*	-0.04	*-2.04*	-0.08	*-2.19*
Weekly sport activities	-0.01	*-1.10*	-0.01	*-1.07*	-0.02	*-1.43*
Daily smoker	-0.03	*-1.82*	-0.03	*-1.65*	-0.03	*-1.49*
Weekly alcohol consumption (index)	0.02	*0.95*	0.03	*1.37*	0.09	*2.52*
Meat	-0.05	*-1.88*	-0.06	*-1.90*	-0.09	*-2.03*
Fruits	-0.01	*-0.95*	-0.01	*-0.57*	-0.03	*-1.36*
Vegetables	0.00	*0.58*	0.00	*0.66*	0.00	*0.14*
Legumes	-0.01	*-1.00*	-0.01	*-1.06*	-0.01	*-0.95*
Unexplained difference	**0.17**	***0.68***	**0.09**	***0.28***	**-0.29**	***-0.67***
Sociodemographics	**-0.06**	***-0.20***	**0.10**	***0.24***	**-0.21**	***-0.38***
Age: 18-35	-0.01	*-0.11*	-0.12	*-0.91*	-0.36	*-2.07*
Age:36-45	-0.09	*-0.71*	-0.10	*-0.67*	-0.08	*-0.38*
Age:46-55	-0.19	*-1.75*	-0.14	*-1.03*	0.07	*0.36*
Age: 55-65	0.26	*2.12*	0.32	*2.10*	0.36	*1.57*
Married	-0.09	*-0.28*	0.14	*0.33*	-0.27	*-0.43*
Kids	0.07	*0.39*	-0.00	*-0.01*	0.06	*0.22*
SES	**-0.08**	***-0.11***	**0.86**	***0.85***	**-0.03**	***-0.02***
Schooling	0.31	*0.41*	0.88	*0.92*	0.83	*0.58*
Income1	-0.24	*-2.08*	-0.02	*-0.20*	-0.03	*-0.15*
Income2	-0.03	*-0.33*	-0.15	*-1.11*	-0.19	*-0.97*
Income3	-0.17	*-1.58*	-0.15	*-1.19*	0.09	*0.50*
Income4	0.12	*1.58*	0.07	*0.84*	0.03	*0.31*
Income5	0.04	*1.10*	0.03	*0.68*	0.02	*0.33*
Income6	0.10	*1.07*	0.08	*0.72*	0.04	*0.27*
Working	-0.21	*-0.77*	0.12	*0.36*	-0.82	*-1.75*
Lifestyle habits	**-1.16**	***-1.81***	**-1.52**	***-1.90***	**-1.21**	***-1.09***
Sedentary job	0.01	*0.07*	0.02	*0.12*	0.02	*0.06*
Weekly sport activities	0.03	*0.36*	-0.03	*-0.38*	-0.07	*-0.63*
Daily smoker	-0.35	*-0.25*	-0.18	*-1.03*	-0.00	*-0.00*
Weekly alcohol consumption (index)	-0.09	*-0.79*	-0.13	*-1.00*	-0.12	*-0.77*
Meat	-0.02	*-0.12*	0.08	*0.40*	0.35	*1.27*
Fruits	-0.87	*-1.80*	-1.59	*-2.65*	-1.51	*-1.84*
Vegetables	-0.24	*-0.59*	0.21	*0.41*	0.05	*0.07*
Legumes	0.06	*1.06*	0.11	*1.60*	0.07	*0.77*
Constant	1.48	*1.32*	0.65	*0.46*	1.17	*0.57*

Table C: Detailed RIFR Decomposition (Men)

	quantile 0.7		quantile 0.8		quantile 0.9	
	mean BMI	***z-stat***	**mean BMI**	***z-stat***	**mean BMI**	***z-stat***
South	28.39	*190.13*	29.76	*158.26*	31.96	*127.92*
North	28.06	*214.79*	29.41	*186.26*	31.64	*148.16*
	Coef.	***z-stat***	**Coef.**	***z-stat***	**Coef.**	***z-stat***
BMI Difference (south-north)	**0.32**	***1.64***	**0.34**	***1.40***	**0.32**	***0.96***
Explained difference	**-0.04**	***-0.42***	**-0.05**	***-0.46***	**0.02**	***0.10***
Sociodemographics	**-0.15**	***-3.50***	**-0.19**	***-3.71***	**-0.19**	***-3.19***
Age: 18-35	-0.08	*-3.67*	-0.09	*-3.53*	-0.10	*-3.40*
Age:36-45	0.00	*0.06*	-0.00	*-0.21*	0.00	*0.02*
Age:46-55	0.00	*0.57*	0.00	*0.55*	0.00	*0.55*
Age: 55-65	-0.05	*-2.86*	-0.08	*-3.09*	-0.08	*-2.45*
Married	0.02	*1.61*	0.02	*1.22*	-0.00	*-0.01*
Kids	-0.04	*-1.92*	-0.04	*-1.46*	-0.02	*-0.47*
SES	**0.24**	***3.88***	**0.26**	***3.46***	**0.34**	***3.34***
Schooling	0.16	*4.23*	0.17	*3.78*	0.23	*3.79*
Income1	-0.01	*-0.35*	-0.00	*-0.03*	0.03	*0.39*
Income2	0.03	*2.25*	0.03	*1.81*	0.03	*1.21*
Income3	-0.00	*-0.12*	0.00	*0.49*	0.00	*0.68*
Income4	0.04	*2.08*	0.03	*1.23*	0.05	*1.75*
Income5	-0.00	*-0.09*	-0.00	*-0.20*	-0.00	*-0.27*
Income6	0.00	*0.26*	0.01	*0.53*	-0.01	*-0.41*
Working	0.01	*1.09*	0.02	*1.27*	0.02	*0.93*
Lifestyle habits	**-0.12**	***-3.26***	**-0.12**	***-2.79***	**-0.14**	***-2.28***
Sedentary job	-0.00	*-0.25*	-0.00	*-0.25*	-0.00	*-0.25*
Weekly sport activities	-0.04	*-2.19*	-0.00	*-2.17*	-0.04	*-2.04*
Daily smoker	-0.02	*-1.82*	-0.03	*-1.74*	-0.05	*-1.91*
Weekly alcohol consumption (index)	-0.00	*-0.37*	-0.00	*-0.37*	0.01	*0.86*
Meat	-0.04	*-2.05*	-0.04	*-0.65*	-0.03	*-0.89*
Fruits	-0.00	*-0.55*	-0.04	*-0.65*	-0.01	*-0.72*
Vegetables	0.01	*0.74*	0.00	*0.46*	0.01	*0.80*
Legumes	-0.01	*-0.68*	-0.00	*-0.30*	-0.02	*-1.01*
Unexplained difference	**0.36**	***1.78***	**0.39**	***1.55***	**0.30**	***0.89***
Sociodemographics	**0.88**	***3.42***	**0.64**	***1.99***	**0.50**	***1.12***
Age: 18-35	0.08	*0.95*	0.13	*1.35*	0.13	*1.04*
Age:36-45	0.06	*0.66*	-0.05	*-0.40*	-0.01	*-0.66*
Age:46-55	-0.11	*-1.22*	-0.15	*-1.33*	-0.33	*-2.06*
Age: 55-65	-0.03	*-0.34*	0.04	*0.32*	0.23	*1.39*
Married	0.61	*2.15*	0.43	*1.21*	0.19	*0.38*
Kids	0.27	*1.96*	0.24	*1.42*	0.38	*1.67*
SES	**0.01**	***0.02***	**0.11**	***0.14***	**0.01**	***0.01***
Schooling	0.45	*0.76*	0.56	*0.76*	0.59	*0.59*
Income1	-0.07	*-0.86*	-0.09	*-0.83*	-0.09	*-0.60*
Income2	0.16	*1.79*	0.20	*1.82*	0.22	*1.44*
Income3	-0.01	*-0.08*	0.01	*0.13*	0.07	*0.47*
Income4	-0.08	*-1.30*	-0.12	*-1.53*	-0.12	*-1.25*
Income5	0.02	*0.42*	-0.01	*-0.19*	-0.05	*-0.66*
Income6	0.01	*0.10*	0.09	*1.00*	0.14	*1.13*
Working	-0.45	*-1.58*	-0.53	*-1.49*	-0.74	*-1.53*
Lifestyle habits	**0.93**	***1.95***	**0.84**	***1.41***	**1.22**	***1.52***
Sedentary job	0.16	*1.14*	0.13	*0.77*	0.09	*0.38*
Weekly sport activities	-0.02	*-0.29*	-0.08	*-0.97*	0.08	*0.78*
Daily smoker	-0.10	*-0.75*	-0.22	*-1.27*	0.08	*0.32*
Weekly alcohol consumption (index)	0.23	*1.64*	0.12	*0.70*	0.04	*0.20*
Meat	-0.08	*-0.60*	-0.06	*-0.35*	-0.56	*-0.24*
Fruits	0.35	*1.11*	0.36	*0.91*	-0.15	*-0.27*
Vegetables	0.42	*1.71*	0.58	*1.90*	1,15	*2.71*
Legumes	-0.01	*-0.35*	0.00	*0.06*	-0.01	*-0.12*
Constant	-1.46	*-1.70*	-1.20	*-1.09*	-1.43	*-0.91*